Artificial Intelligence in Cardiac Disease Diagnosis: A Comprehensive Investigation

Tianhao Zhang[a]
Robot Engineering, Shenzhen Technology University, Shenzhen, China

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Abstract: In the medical field, the use of massive data to assist medical diagnosis is an inevitable trend of development. In the diagnostic process, various machine learning algorithms are utilized to achieve assisted medical diagnosis of cardiac diseases based on a large amount of data sources acquired in clinical practice. This paper introduces the role of artificial intelligence (AI) in the diagnosis of cardiac diseases, and describes the utilization of various traditional machine learning and deep learning models to improve diagnostic efficiency and accuracy. By examining large amounts of clinical data, including electronic health records and imaging, AI has a unique advantage over traditional diagnostic methods in terms of high accuracy and efficiency. This paper explores a variety of AI diagnostic frameworks. In addition, this paper explores the limitations and challenges faced by AI in the field of medical diagnostics today, including issues of data quality, model interpretability, and population generalization, and also proposes corresponding approaches such as federated learning and Explainable AI are also proposed as possible solutions to overcome these obstacles. This paper not only demonstrates the current progress of AI in the field of cardiac diagnosis, but also makes predictions about its future prospects.

1 INTRODUCTION

Heart disease is the disease that the causes are attributed to structure or function of the heart, including myocardial infarction, arrhythmias, heart failure, and various other types. It has become one of the main causes of disability and death worldwide with the trend of population aging and the change of lifestyle. Millions of people die each year due to heart disease, highlighting the importance of diagnosing heart disease.

Relying on the experience of physicians and a series of examinations such as electrocardiograms and echocardiograms, traditional medical diagnostic methods have certain limitations, such as slow diagnostic process, misdiagnose, and various other types. In addition, these methods incur high labor costs. Consequently, an increasing number of researchers tend to explore approaches with Artificial Intelligence (AI) to improve the diagnostic methods since it can effectively discover the correlations within vast amounts of data by mimicking human learning and reasoning processes (Qiu, 2019; Qiu, 2022).

AI is widely applied to many fields including healthcare (Li, 2024; Liu, 2023; Zhao, 2023). And this transformative shift brings about a new era in medical diagnosis, patient care, and treatment personalization. A systematic review by Kakas et al. underscores the latest developments in Explainable artificial intelligence (XAI) solutions for medical decision support, emphasizing the necessity of increased collaboration between medical and AI experts to devise frameworks guiding the design, implementation, and evaluation of XAI solutions in medicine (Prentzas, 2023). In addition, research by Feng et al. discusses common applications of AI in medicine, including virtual assistants, AI-augmented diagnostics, and medical robots (Zhao, 2022). Moreover, High-Performance Computing (HPC) technologies show great potential in processing the vast amounts of data characteristic of modern medical practice (Koch, 2023).

In addition to these applications, AI is widely used in the field of cardiac diagnosis. For example, Butler

[a] https://orcid.org/0009-0006-9812-4889

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et al. developed Electrocardiography Artificial Intelligence (ECG-AI) models for predicting fatal coronary heart disease using 12-lead and single-lead ECG data, demonstrating the potential of AI for early detection and intervention (Butler, 2023). Similarly, Nedadur et al. explored the use of AI in echocardiography, particularly in valvular heart disease, demonstrating how AI can improve diagnostic accuracy through automated analysis (Nedadur, 2022). Maambo et al. described an AI medical diagnostic system that utilizes healthcare data to predict heart disease risk, using data mining algorithms to improve the diagnostic process (Maambo, 2022). Janik et al. investigate deep learning models for cardiac Magnetic Resonance Imaging (MRI) segmentation, focusing on the importance of model interpretability to make AI-assisted diagnosis more transparent and understandable (Janik, 2021). Finally, Thoenes et al. discuss the use of AI in the management of aortic valve disease, emphasizing how AI can support early diagnosis and efficient treatment planning (Thoenes, 2021). Together, these examples highlight the diverse and impactful applications of AI in the diagnosis, treatment, and management of heart disease, marking an important step in cardiology's use of technology to improve patient prognosis.

The review is divided into following sections. The second section firstly provides an overview of current mainstream methods for cardiac disease diagnosis. Following this is an analysis of those methods, including their advantages and disadvantages, the difficulties they encounter and the main algorithms they used. The last section is conclusion of the current AI field of the disease diagnosis, and its future prospects.

2 METHOD

In this section, the current mainstream AI-based models for diagnosing heart disease, including traditional machine learning, as well as deep learning models, will be demonstrated.

2.1 Framework of AI-Based Heart Disease Diagnosis

In order to improve the accuracy of diagnosing heart disease as well as the efficiency of the diagnosis and to improve the predictive ability, an AI-based diagnostic framework for heart disease should contain multiple steps. Typically, a typical framework is going to contain the following aspects. The first step is data collection and preprocessing. The sources of data are generally large datasets including Electronic Health Records (EHR), imaging data (e.g., echocardiograms, MRIs, Computed Tomography (CT) scans), genomics, wearable devices, and patient-reported data. However, generally these data are generally not directly available as inputs to the training model, and before that, they need to be cleaned, normalized and anonymized so that the model can recognize them effectively. This step may include dealing with missing values, correcting errors and normalizing formats. Next, the model needs to extract the most relevant features that will help to accurately diagnose heart disease (e.g., patient demographics, clinical parameters, lab results, imaging features) and will convert the raw data into a format that can be efficiently processed by AI algorithms, often using techniques such as Principal Component Analysis (PCA) for dimensionality reduction or customized algorithms for extracting meaningful attributes from complex data such as images. In the third step, appropriate artificial intelligence models such as Machine Learning (ML) algorithms (e.g., decision trees, support vector machines, random forests) and Deep Learning (DL) models (e.g., convolutional neural networks for image analysis) are selected based on the characteristics of the data. Preprocessed data is fed into selected models to learn patterns related to heart disease. This involves dividing the data into training and validation sets to iteratively improve the accuracy of the model. In order to verify the validity of the model, it needs to be validated and tested after the training is completed. Usually, this step involves tuning the model parameters using a separate part of the dataset (in the dataset, but not involved in model training). The performance of the model on the test set is then evaluated to assess its generalizability and accuracy in diagnosing heart disease. Performance metrics may include accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (ROC).

For this type of AI models, there is also a need to integrate them into the clinical workflow by integrating the AI models into the clinical environment, for example by embedding them in electronic medical record systems or diagnostic tools to support healthcare professionals. User-friendly interfaces also need to be developed to enable clinicians to enter data, receive predictions and visualize results in an intuitive way.

To ensure that it remains accurate and effective over time, the developers involved also have to continuously monitor the performance of the AI system in the real world. They also need to incorporate feedback and outcome data from clinicians to refine and update the model and ensure that it adapts to new data and changing clinical practices.

2.2 Traditional Machine Learning-Based Heart Disease Diagnosis

2.2.1 Random Forest Classifier

The Random Forest classifier operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes of the individual trees. A key aspect of this method is its use of "bagging" (bootstrap aggregating) to promote variance reduction across trees without increasing bias. This is achieved by randomly selecting subsets of the training data, with replacement, to build each tree, ensuring diversity. The Random Forest then utilizes feature importance scores derived from the trees to identify and select the most relevant features for heart disease prediction. And specifically in the field of heart disease diagnosis, Saranya et al. build on this by tuning the hyperparameter through grid search approach and successfully increasing the diagnostic accuracy to 96.53%. The advantage of this approach is that it is able to handle large datasets with high dimensionality and inherent feature selection capabilities, making it well suited for complex health datasets (Saranya, 2023).

2.2.2 Support Vector Machine (Svm)

Support Vector Machine works by mapping input features into high-dimensional feature spaces where it becomes easier to linearly separate data points belonging to different classes. The core principle of SVM is to find the optimal separating hyperplane that maximizes the margin between the closest points of different classes, known as support vectors. This method is particularly effective for heart disease diagnosis due to its ability to deal with non-linear boundaries through the use of kernel functions (e.g., linear, polynomial, and radial basis function). Suresh et al. demonstrated a hybrid approach that combines the feature selection strength of Random Forest with the classification power of SVM, achieving an accuracy of 98.3%. The hybrid model benefits from SVM's robustness against overfitting in high-dimensional spaces and its capacity for handling nonlinear relationships, crucial for accurately classifying medical data (Suresh, 2022).

2.2.3 Hybrid Random Forest with a Linear Model

In the exploration of deep learning-based methods for heart disease diagnosis, a notable advancement was introduced by Dwarakanath B. and colleagues, who proposed a novel approach that combines feature selection with hybrid deep learning for heart disease detection and classification (FSHDL-HDDC). This method utilizes an Attention-based Convolutional Neural Network (ACNN) combined with Long Short-Term Memory (LSTM) specifically for analysing medical data. By employing a feature selection method based on the Elite Opposition-based Squirrel Search Algorithm (EO-SSA), it identifies the optimal subset of features. This approach has demonstrated exceptionally high accuracy in the field of heart disease diagnosis, achieving a maximum accuracy level of 97.72%. Its strength lies in its ability to deeply analyse complex patterns in medical data, thereby improving the precision and efficiency of heart disease predictions, making it highly suitable for handling health datasets with high dimensionality and complexity (Mohan, 2019).

2.3 Deep Learning-Based Heart Disease Diagnosis

This year has seen breakthroughs in the field of deep-based learning. Deep learning has unique advantages over traditional machine learning. First, deep learning models typically have more parameters and hierarchies, which means they can learn automatically and extract more complex, abstract features from data. Second, deep learning models have more powerful representations, which enables them to capture complex connections in large datasets and thus achieve more accurate predictions. In addition, thanks to back-propagation algorithms, deep learning models can automatically tune model parameters to optimize performance, and this end-to-end training approach makes model construction and tuning more efficient. Nevertheless, deep learning models face problems such as high consumption of computational resources and the training process is so abstract that it is difficult to observe compared with traditional machine learning models. Three effective deep learning models will be described below (Dwarakanath, 2022).

2.3.1 Hybrid Deep Learning for Heart Disease Detection and Classification

This model combines attention-based convolutional neural network (ACNN) with long short-term memory (LSTM) to analyse medical data efficiently and accurately. The key to this approach is a special selection method that identifies the best subset of features based on elite opposition-based squirrel search algorithm (EO-SSA). This method is proposed by Dwarakanath B. et al. for heart disease detection and classification (FSHDL-HDDC) in eHealth environment. With this method, heart disease can be predicted with up to 97.72% accuracy. This demonstrates the potential of combining FEATURE SELECTION algorithms and DEEP LEARNING models (Kusuma, 2022).

2.3.2 BiDLNet: Integrated Model for ECG-Based Diagnosis

The BiDLNet model is an integrated deep learning framework proposed by Kusuma et al. , which utilizes capabilities using electrocardiogram (ECG) data to improve diagnostic capabilities and predictive accuracy. BiDLNet employs a discrete wavelet transform to extract two levels of features from the data, followed by an ensemble classification scheme that combines predictions from various deep learning models. In terms of achievements, the model achieved excellent results in dichotomization and multichotomization of heart disease, 97.5% and 91.5%, respectively. The method exemplifies the effectiveness of integrating multiple deep learning techniques to improve the accuracy and reliability of diagnosing heart disease from ECG signals (Hamad, 2021).

2.3.3 Long Short-Term Memory (LSTM) Networks for Feature Extraction

LSTM networks are designed to avoid the long-term dependency problem typical of standard recurrent neural networks, making them adept at processing sequences of data for tasks like heart sound signal analysis. These networks introduce memory cells that can maintain information in memory for long periods of time. Each cell decides through structures called gates (input, output, and forget gates) whether to retain or discard information based on the strength and relevance of incoming signals. Guven et al. Guven and Uysal leveraged this capability by combining both short-term features, extracted from five-second heart sound fragments, and long-term features from the entire signal.This approach can combine the nuances of individual pieces of information with the overall pattern of information, benefiting from the ability of LSTM to capture and learn from these complex temporal dependencies, so that the diagnostic accuracy of heart disease can be greatly enhanced (Guven, 2023).

3 DISCUSSION

Despite the breakthroughs in the field of diagnosing heart disease, AI is still limited and faces many challenges. Here are some of the major limitations and challenges, as well as possible solutions.

3.1 Challenges and Limitations

3.1.1 Data Quality and Availability

Being able to guarantee the availability of high-quality and annotated medical datasets is a major challenge in the application of machine learning and deep learning models. Because, Cardiac imaging and EHR often contain sensitive patient information, which is likely to raise privacy and ethical concerns. In addition, the quality of residual datasets and incomplete records can hinder the training of models and affect the accuracy of diagnosis. These data issues are the current need to be urgently addressed.

3.1.2 Model Interpretability

A long-standing difficulty in the field of deep learning models is the "black box" problem, where developers cannot know the decision-making process of a model because of the abstract nature of the model, which makes it difficult to trust the predicted results to clinicians and patients, and this lack of interpretability hinders the application of AI tools in clinical practice. Although there are currently some visualizations available that allow the detection of the model's decision-making process, the "black box" is still a major problem facing deep learning models today.

3.1.3 Generalization Across Diverse Populations

Inevitably, bias is present in training datasets, which makes it difficult for machine learning models and deep learning models to generalize their scope of action to different populations. Models trained on a specific population dataset may not perform well on data from other races or age groups, which may lead to inaccurate diagnoses.

3.2 Future Prospects and Possible Solutions

3.2.1 Federated Learning and Data Privacy

Federated learning is known to be a promising solution to the problem of data privacy and residual data quality. The most important mention of federated learning is decentralization. The general principle of the model is that it takes its dataset from multiple decentralized devices and servers and trains the model on these devices simultaneously, which means that the data is all stored locally on the devices without the need to centralize the data centrally for training. This approach not only improves privacy, but also creates robust models that can learn from different datasets. Additionally, enhancements in hardware capabilities and transmission mechanisms are necessary to effectively integrate with federated learning algorithms (Deng, 2019; Deng, 2023; Sugaya, 2019).

3.2.2 Explainable AI (XAI) for Model Interpretability

The complexity of DL models often makes them appear as "black boxes," making clinical adoption challenging due to the lack of interpretability. Explainable AI (XAI) aims to make the decision-making process of these models transparent and understandable to clinicians. By providing insights into the models' inner workings, XAI facilitates trust and enables clinicians to make informed decisions, ensuring that AI acts as a support tool rather than an opaque decision-maker.

3.2.3 Bias Mitigation Strategies for Generalization Across Populations

AI models can inadvertently learn and amplify biases present in the training data, leading to poor generalization across different demographics. Bias mitigation strategies involve techniques for identifying and reducing these biases during the model training process. By employing such strategies, researchers and developers can create AI systems that perform equitably across diverse patient populations, ensuring that the benefits of AI in cardiac diagnosis are accessible to all.

4 CONCLUSIONS

This study details the progress and achievements of artificial intelligence in the field of cardiac diagnosis, emphasizing its potential to possess superiority over traditional methods. This study provides an in-depth look at various approaches from machine learning to deep learning models, including their principles, applications in heart disease diagnosis, and achievements. These methods include Random Forest classifier for feature selection, Support Vector Machine for data classification and other advanced methods. Also, this thesis lists the challenges and limitations faced by the field of Artificial Intelligence in the field of cardiac diagnosis today and also gives some possible promising solutions.

However, this study can also have some limitations, for example, ethical considerations and patient privacy issues related to AI in healthcare can be further explored. The massive amount of data required for AI models raises significant privacy concerns, and this paper would benefit from discussing how these challenges can be addressed. In addition, the impact of AI on the healthcare workforce, including the need for reskilling and potential job displacement, remains unaddressed but is a key area for future exploration.

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